XRD CHARACTERIZATION OF ANTARCTIC GLACIAL DRIFT DEPOSITS: IMPLICATIONS FOR QUANTIFYING WEATHERING PRODUCTS ON EARTH AND MARS. C. Demirel[1], G. S. Soreghan[1], N. McCollom[1], A. S. Elwood Madden[1], K. Marra[2], and M. E. Elwood Madden[1], [1]School of Geology and Geophysics, University of Oklahoma, Norman, OK 73072 (cansu.demirel@ou.edu), [2]USGS

Introduction: The MSL (Mars Science Laboratory) rover Curiosity provided the first X-ray Diffraction (XRD) mineralogical data on Martian rocks and regolith via the CheMin instrumentation to elucidate surface alteration processes, thus enabling interpretations of the paleoclimate of Mars [1]. Additional geochemical and stratigraphic data from ancient lacustrine mudstones at Gale Crater indicated a transition from cold and/or arid to more temperate conditions on early Mars [2]. This combined data can provide insight into the mode of weathering, availability of water, and past habitability on early Mars [1,2]. In order to better understand how weathering occurs in cold, hyper-arid environments we are analyzing glacial sediments from Antarctic McMurdo Dry Valleys (MDV) since the MDVs are one of the best terrestrial analogues for Mars surface conditions [3,4].

Recent studies revealed extensive chemical weathering in the hyper-arid Antarctic MDVs during the short melt season [5,6]. Previous XRD analyses of glacial meltwater stream and drift deposits targeted silicate mud fractions [6], as fine-grained sediments produced by glacial grinding have high surface area, and thus high potential chemical reactivity [7]. Similar to Martian rocks and soils, the Antarctic MDV samples contain abundant plagioclase, pyroxene and phyllosilicate phases (biotite, chlorite, illite, smectite, etc.) with other minor or major (quartz, amphiboles, etc.) components [6,8-10]. However, variations in sample preparation may cause discrepancies in quantitative analyses [11,12]. In addition, using different software packages and/or mineral databases may also significantly affect interpretations [11]. Assessing these differences and the degree of variation observed in quantitative mineral analyses is important for understanding weathering products and making interpretations on the availability of water on planetary surfaces [1,10]. Therefore, optimizing quantitative analyses to account for software or sample-preparation effects is essential.

This study investigates a glacial drift deposit from Taylor Valley, MDV, by comparing the effects of both sample processing variations and different software packages for quantitative analyses.

Methods: The drift sample was collected in January 2010, adjacent to Howard Glacier meltwater stream in Taylor Valley [5,6]. This deposit contains pre-Last Glacial Maximum (LGM) products of wet-based Ross Sea drift and the fine-grained aeolian sediments generated via the most recent cold-based glaciers [6,13]. The sample was wet sieved to obtain the <63μm (mud) fraction, and treated with glacial acetic acid and H_2O_2 to remove carbonate and organic fractions, respectively [6]. Samples were analyzed with a Rigaku Ultima IV XRD with Cu radiation source and graphite monochromator, using the Bragg-Brentano method (2-70º 2θ angle interval). Analyses were run with 0.02º step size and 2 s counting time, using variable slits. Random mounts of each mud batch were analyzed in triplicates in standard glass sample holders. Additionally, a zero-background random mount was analyzed for each batch and respective quantitative results were included in statistical calculations (Table 1). Separate subsamples were micronized and mixed with corundum standard (20% mix, using the specific corundum powder recommended by Eberl [14]). These samples were also analyzed in triplicate. An oriented mount was also prepared using the filter-peel method to identify clay minerals.

Mineral phases were interpreted using the Rietveld refinement with MDI Jade [11] and RockJock method with ClaySIM software [14]. We used the same selected phases from ICDD-PDF-4+, AMCSD and MDI500 databases for each evaluation to be consistent and avoid difficulties in the refinements [11]. ANOVA and Tukey statistical tests were further run using R software on the whole (n=22) and software-based comparative sample populations (n=11) for each mineral phase to assess the significance of variations between data sets [15].

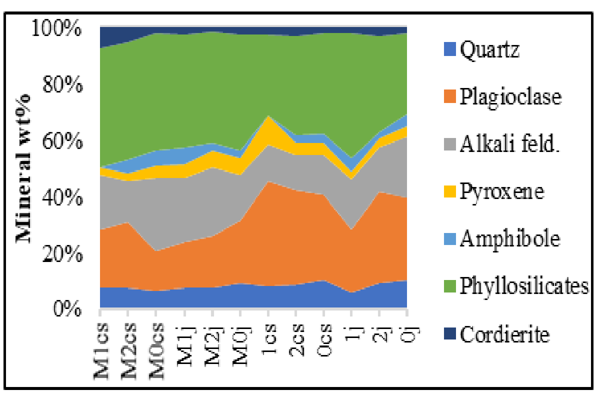
Results and Discussion: Overall bulk mineralogy showed that a majority of the sample is composed of primary minerals (58%), with the presence of plagioclase (labradorite > anorthite > albite > andesine > oligoclase), alkali feldspars (microcline > orthoclase > anorthoclase), quartz, pyroxenes (diopside > augite) and amphiboles (tremolite > hornblende) in the given abundance order (Table 1). Phyllosilicates composed about 43% of the drift mineralogy, dominated by biotite, chlorite and illite, with minor muscovite and mixed-layer clays with smectite. These results are consistent with previous reports [6,8-10]. Additionally, cordierite was detected in all random mounts and reported here for the first time in Antarctic drifts, which might be inherited from metamorphic bedrock [16]. Numerous random mount runs resulted in varying peak intensities, which are most profound for feldspars and phyllosilicates. ANOVA and Tukey statistics (P values >0.05) show no significant variation between data sets.

Software-based Variations: Using different software for mineral interpretation produced the biggest variations in feldspar and phyllosilicate phases (Table 1, Figure 1). This might be due to software and quantification method-based differences. The Rietveld method may cause misinterpretations of the weight % of phyllosilicates. Additional difficulties in quantifying clay minerals may result from a low degree of preferred orientation within random mounts, since we did not chemically treat them specifically for clay mineral analysis [12]. We found that the Rietveld method yielded higher standard deviation (SD) for phyllosilicates within our dataset (Table 1). More specifically, SD for biotite (6%) was 2 folds higher than the RockJock method. On the other hand, overlapping peaks complicate identification of individual feldspars with MDI Jade, which potentially gave >5% SD. Additionally, ClaySIM interpretations gave the highest SD for plagioclase feldspars (Table 1). However, it is important here to note that overall phase identification using RockJock method is limited due to the small number of minerals available in the database [14].

Table 1. Mean and standard deviation (SD) of weight% minerals for overall (n=22), ClaySIM (n=11) and Jade (n=11) groups

	ClaySIM		Jade		Overall	
	Mean	SD	Mean	SD	Mean	SD
Plagioclase	27.2	6.2	24.9	5.3	26.1	5.9
Alkali feldspar	14.9	4.0	16.1	5.1	15.5	4.6
Quartz	8.0	0.9	8.0	1.4	8.0	1.2
Pyroxene	4.9	2.1	4.4	0.9	4.6	1.7
Amphibole	3.1	2.1	3.5	1.0	3.3	1.7
Phyllosilicates	38.6	4.6	41.2	5.4	39.9	5.1
Cordierite	3.3	1.9	1.9	0.8	2.6	1.6

Figure 1. Mineralogy of micronized and mud batches of the drift sample (M: micronized; 0: zero-background holder, cs: ClaySIM; j: Jade)



Implications for Weathering on Earth and Mars: Overall statistics indicate no significant variations between different evaluations. However, weathering extent depends on the phases that show the biggest deviations in Table 1, according to their susceptibility to chemical reactions [17]. Feldspar downstream abundance can be used to estimate chemical weathering extent in hyper-arid planetary settings [5,6,8]. Presence of smectites is commonly related to availability of standing water, and dominance of chemical weathering reactions [10]. Additionally, our results show good precision for amphiboles, as weight % SD values were relatively lower within all statistical sample groups (1-2 %; Table 1). Bishop et al. [3] argued that tremolite was detected in Antarctic sediments with their CheMin-like instrument, but not with traditional XRD instruments. Our analyses detected tremolite in 15 mounts out of 22. Tremolite may indicate water-limited weathering of olivine, which is abundant on Mars [3]. Our combined findings show the importance of running replicates and optimizing refinement parameters. Therefore, our results will serve as a guide for assessing the precision of future XRD-based studies on Earth and Mars surface weathering processes and paleoclimate.

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